Toward an Enhanced Learning Through Existing Massive Open Online Courses Platforms

Amal Battou

Abstract Massive Open Online Courses (MOOCs) attract many actors all over the world, especially those of higher education. So, there is a need to enhance and to tailor the instruction of MOOCs to meet the learner's needs. This chapter investigates the MOOCs system by reviewing the available literatures and suggesting a framework based on Analytic Hierarchy Process (AHP) algorithm for an adaptive learning through existing MOOCs. In this suggested framework, a variety of aspects including choice of learning path, learner satisfaction, and achievement are considered to present an adequate list of existing MOOCs to a learner. The main aim of this framework is to improve learning effectiveness and ensure learning quality.

Keywords Learning quality · Learner-centered design · Long-term learning · MOOC · Enhanced learning · AHP approach

1 Introduction

Undoubtedly, MOOCs platforms offer many opportunities to support e-learning and learning, from managing the learning and training process to monitoring the evaluation process. To make relevant MOOCs, diverse backgrounds such as content developers, domain experts, instructional designers, pedagogues, graphic designers and programmers, etc. are involved. MOOCs are expensive to produce. It involves considerable amount of time investment of several actors. If some large universities can afford them, it is not the case for smaller ones [4].

In addition, criticisms of the low rates of completion of MOOCs are still current. As with any training, the success of a MOOC is measured on the basis of what has been learned, understood, and internalized. Nevertheless, the task is particularly

A. Battou (✉)
IRF-SIC Laboratory, Faculty of science, Agadir, Morocco

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laborious because of the lack of individualized training and evaluation. This is mainly due to audience size [10].

Thus, we had the idea to reuse and capitalize existing MOOCs according to their reuse policy and our requirements. At the same time, we will develop courses that meet the skills of our team. Afterward, we will evaluate and choose courses that will be adapted to each learning profile.

Given the diversity of existing MOOCs, we thought about setting up an interactive and adaptive platform that represents the mediating layer between the learner and the MOOCs platforms. The purpose of this platform is to make the decision and to evaluate some amount of information to display the list of courses of a pedagogical course in adequacy with the information and the characteristics of each learner. In addition, this platform must be equipped with technological means enabling users to interact through the man–machine interfaces during the course. The questions that arises in this case is how the platform will evaluate multitude criteria (a list of existing MOOCs, learner needs, capacities, preferences, etc.) to choose the appropriate courses for a learner? How to implement the notion of adaptivity in the learning process in a pedagogical path?

Our readings allowed us to opt for *decision support systems* (DSS). These systems will allow us to take into account a multitude of criteria (information on existing MOOCs and open at time t, information about a student, information on the educational path, etc.) to choose the optimal solutions from a set of possible solutions. Also, the system must take into account information from user feedback and information from tools for tracking of actions performed by learners.

The remainder of this chapter is structured as follows. We will firstly present the AHP method. We discuss next the MOOC reusability concept. Afterward, we explore and present the framework and its features. Finally, we discuss the ability of this framework to improve learning effectiveness and ensure learning quality.

We will first begin by presenting an overview of the state-of-art literature on DSS. Then, we present the AHP method. We then discuss the concept of reusing existing MOOCs as a solution of effectiveness learning. Next, we explore and present the proposed framework architecture that implements the principles of AHP.

2 Multicriteria Decision Support Methods

Multicriteria decision support methods are relatively new and growing scientific approaches. These approaches are solicited where we are confronted with a complex situation, and the decision is based on several decision criteria and possible solutions.

The decision in the presence of multiple criteria is difficult because the criteria are often conflicting. For this, several multicriteria decision support methodologies have been developed, and we quote as an indication: Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Data Envelopment Analysis (DEA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), etc.

[7, 11]. The diversity of these methods lies essentially on the synthesis of the information contained in each criterion [3].

The exhaustive study of these methods goes far beyond the scope of this work. Thus, we have relied on comparative studies of the most widespread methods and the choice of the best method to use in a given context. We quote as an example the works of Hammami [5] and Zouggari [16].

In general, the majority of these methods operate in 4 main steps [3]:

- **List the potential actions**: this step defines possible contributions to the overall decision that can be considered independently and serves as a point of application for decision support;
- **List the criteria to consider**: this step involves determining contribution and effects that impact the decision process;
- **Establish the table of performances**: this table is constituted, in rows, of the alternatives and, in columns, the criteria to be taken into account for the decision-making; and
- **Aggregating performance**: this step is about establishing a formalized representation of the appropriate global preferences to the problem of decision support.

The present work focuses on the AHP approach, which is the subject of the following paragraph, for the selection of the most appropriate courses taking into account a certain set of criteria (the learning profile, the existing MOOC data, etc.). Indeed, the final decision to present to the learner requires a comparison between all the input criteria in order to prioritize the courses and classify them according to their relevance.

2.1 The AHP Approach

2.1.1 Presentation of the Approach

Analytic Hierarchical Analysis (AHP) is a theory of complex decision analysis proposed by Thomas Saaty [13]. Recognized by its simplicity of application, this method allows the most credible decisions taking into account several factors. The AHP is considered one of the main mathematical models currently available to support the theory of decision [15].

The AHP structures the criteria in a hierarchical manner and then compares them in pairs to design, prioritize, justify, and choose the right solution for the most complex situations. This method has its advantage of its similarity to the decision-making mechanism of the human being, namely decomposition, judgment, and synthesis [2].

AHP is easy to implement, and it is widely used for solving multiple selection problems. This method makes it possible to split the most complex decision problems in the form of hierarchical levels. The scale of values chosen expresses the preferences of decision-makers, and it also makes it possible to rally qualitative and quantitative criteria [8], where each criterion contributes to the final decision [14].

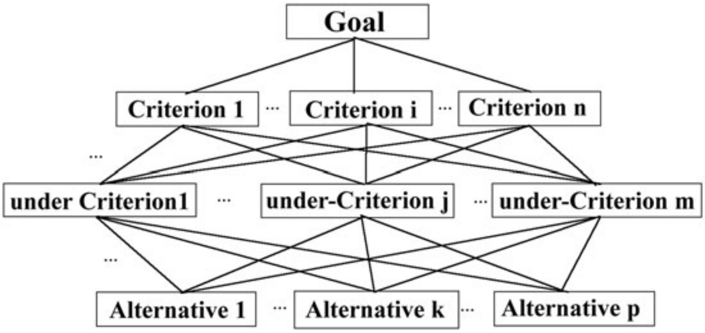

Fig. 1 Hierarchical architecture of the AHP approach

2.1.2 Principle of the Approach

The approach is to first designate the general objective on which we will make our decision and then the possible solutions or alternatives and criteria to consider [7]. In some cases (complex decisions), we can have several levels of criteria (criteria, sub-criteria, etc.) Figure 1 presents the hierarchical architecture of the AHP method.

After having determined the objective criteria, under criteria, and the various alternatives, the next step is to evaluate by peer all the criteria of each hierarchical level compared to the higher hierarchical level.

However, this method had some criticisms mainly on the fact that the association of a numerical scale with another semantics is restrictive; then, it introduces imprecise numerical values. The method has experienced several extensions to attempt to remedy some of the criticisms, the case of taking into account the uncertainty (stochastic AHP), and the blur (AHP blur) in the expression of the judgments [6].

In this work, we only present our system according to the AHP process. Other Phd-student work focuses on the use of fuzzy logic in combination with AHP. These works are subject of publication such as [1].

3 Toward Reusing Pre-existing MOOCs

3.1 Working Context and Demands

Several Moroccan universities, in particular IBN ZOHR University, have adopted several projects to implement and integrate information and communications technology (ICT) into the learning process in order to offer learners a variety of resources (software, multimedia, etc.). The main aim of this use is to increase learners' motivation to learn and contribute to improving the quality of learning and teaching. We also note the use of platforms and websites offering online courses (LMS, E-learning, etc.) and the proposal of diplomas and certificates via distance learning courses and the famous MOOCs that offer massive courses and open for everyone. These have revolutionized the world of education by combining technological and pedagogical aspects in their products (courses, assessments, etc.) and by imposing themselves as a solution to the problems of the low rate of supervision and the growing number of students.

However, all technologies have limitations and weaknesses [9]. As an example, we mention the MOOCs that have solidly established themselves in the educational panorama, especially in foreign universities (Fun, Coursera, etc.). Many works highlight the low completion rate which reflects the dropout rate recorded at the end of each course, while the number of enrolled in the latter at the start is very important.

Given the constraints highlighted in the introduction, we thought to capitalize the existing MOOCs in parallel and we will develop course materials in line with our specialties. Several questions arise and we quote them as an indication: how can we arrange a pile of courses from the MOOCs with the courses developed by our team? which are the criteria to take into account for the generation of the list of courses to select only course in adequacy with a given profile in a specific time? etc.

Below, we will try to bring some elements of answer to these questions.

3.2 Conception of the Proposed Solution

The main goal of our work is to design an intelligent platform to:

- Search courses that meet several criteria set at entry
- Generate a list of course choices relevant to a learning profile at a time t
- Ensure the interactivity of learners between themselves and with the teaching staff
- Track learner progress through tracking interactions with the system.

The learner is led, during his first visit to the system, to create his profile by filling information in a registration form. This profile contains:

- **Domain-independent data (DID)**: these data are rather permanent and include information about the learner's initial knowledge, purpose and plans, cognitive abilities, learning styles, preferences, academic profile (technological studies, knowledge of literature, artistic abilities, etc.), etc.
- **Domain-dependent data (DDD)**: these data are rather dynamic and change as the learner progresses in learning. They essentially contain information on the knowledge/skills acquired for a given field.

After initializing his profile, in a connected learner environment, learner will choose the concept he wants to study. If this concept is part of the courses developed internally, the content will be displayed to the learner taking into account his profile. Otherwise, the platform will launch a request concerning the concept requested

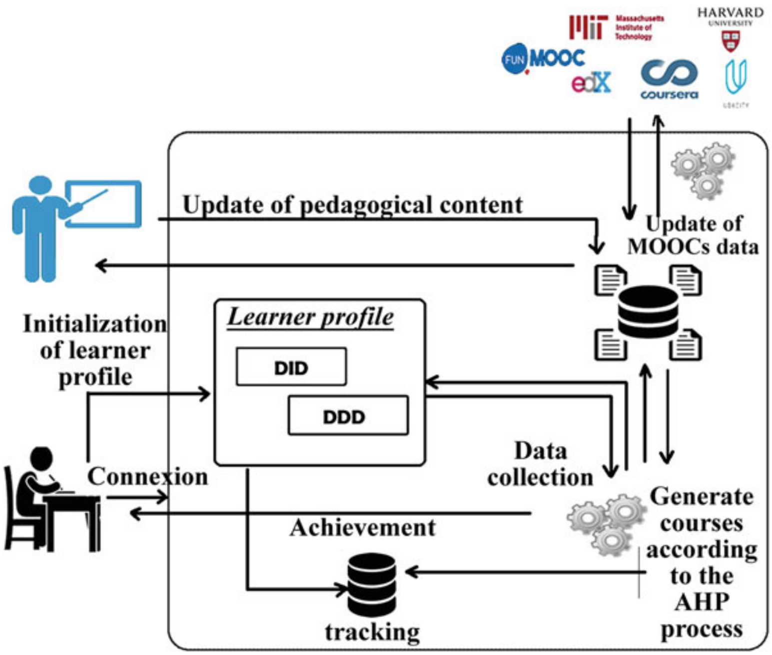

Fig. 2 Architecture of the proposed framework

to the mediation layer with the platforms of the existing MOOCs and chosen beforehand. All the results obtained by this request are transmitted to the generator that will apply the AHP process according to the criteria we have previously determined (learning profile, data on the MOOCs, etc.). The result of the optimal courses will be presented to the learner.

The proposed system architecture is given in Fig. 2.

The list of courses to be generated by the AHP process is based on the following criteria:

- Language of learning (L)
- Course Availability (D)
- Level of knowledge / skill (C)
- Institution responsible for the course (E)
- Prerequisites of a course (P)
- Free/paid course (GP)

Based on this information, we will extract all the data that meet the criteria and prioritize them using the AHP method. After completing his apprenticeship, the learner is asked to answer some questions (satisfied or not, suggestions to improve the platform, etc.) in the form of a survey to ensure the improvement of our platform.

3.3 A Worked-Through Example Showing the Use of AHP Approach

We will take as an example the “IT security” course provided for SMI6 students. The objective of this course is to acquire the fundamental concepts of the IT security.

To ensure such an objective, the criteria mentioned above must be taken into consideration, namely language of learning (L), availability of courses (D), institution responsible for the course (E), level of competence/knowledge (C) , prerequisites of a course (P), and free/paid course (GP). Suppose that the possible courses are cours_1, cours_2, and cours_3. The diagram corresponding to this objective given in Fig. 3.

The next step is to peer-evaluate all the criteria and determine the decision criteria matrix while determining the importance of each criterion over another, according to the following scale of value (see Table 1).

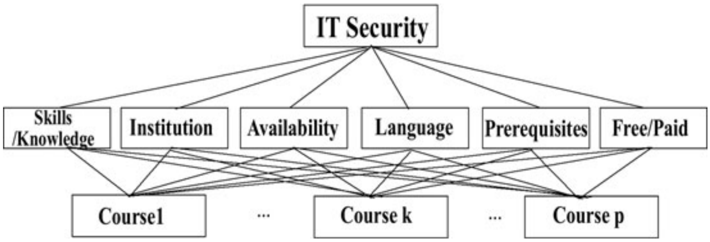

Fig. 3 A worked-through example of the course IT security

Table 1 Value scale proposed by Saaty [12]

Degrees of importance	Definition	Description
1	Equal importance of the two criteria	Two criteria contribute equally to the objective
3	One criterion is a little more important than the other	The experience and the personal judgment slightly favor one criterion compared to another
5	One criterion is much more important than the other	The experience and the personal judgment favor one criterion compared to another
7	One criterion is very strongly more important than the other	One criterion is strongly favored over another and its dominance is demonstrated in practice
9	One criterion is extremely more important than the other	The evidence favors one criterion over another
2,4,6,8	Intermediate values between two judgments	When we need to make a compromise between two criteria to refine the judgment

Table 2 Standardized matrix

	E	C	D	L	P	GP	Medium
E	0.043	0.044	0.015	0.015	0.531	0.206	0.142
C	0.257	0.265	0.131	0.149	0.177	0.265	0.207
D	0.386	0.265	0.131	0.522	0.035	0.088	0.238
L	0.009	0.132	0.026	0.075	0.059	0.147	0.075
P	0.300	0.265	0.654	0.224	0.177	0.265	0.314
GP	0.006	0.029	0.044	0.015	0.020	0.029	0.024

We notice that when a criterion "i" is given when it is compared to a criterion "j," it will have the opposite value when it will be compared to criterion "i." This allows us to build the following comparisons matrix:

	E	C	D	L	P	GP
E	1	1/6	1/9	1/5	3	7
C	6	1	1	2	1	9
D	9	1	1	7	1/5	3
L	1/5	1/2	1/5	1	1/3	5
P	7	1	5	3	1	9
GP	1/7	1/9	1/3	1/5	1/9	1

Subsequently, to obtain the weight of each of the criteria (the greater the value of the weight, the greater the importance of the criterion), it is necessary first of all to construct the standardized matrix; for this, it is necessary to calculate the sum of each column:

$$\sum_{i=1}^{n} C_{ij}$$

Then we divide each of the values of the column by this sum: $\frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}}$. The standardized matrix is thus obtained as shown in the table below (see Table 2: standardized matrix)

Next, we calculate the weight of each criterion by calculating the average of the corresponding line:

$$\frac{\sum_{j=1}^{n} N_{ij}}{n}$$

with $n = 6$ in our case. We will obtain the following averages:

Criterion	*Average*
E	0.142
C	0.207
D	0.238
L	0.075
P	0.314
GP	0.024

The next step is to establish matrices for each decision criterion for each learner to compare courses in the area of network security.

Finally, we will obtain a matrix of solution that we will multiply by the matrix of averages. This last operation will allow us to classify the courses offered to each learner in priority order.

For the first version of the system, we emphasize that the framework allows to generate a list of MOOCs according to the needs of learners and the pedagogical criteria. In terms of the applicability of the approach, the preliminary results indicate that the method is useful and gave satisfactory result. In addition, we try in our framework to focus and to evolve learners. However, it was a bit difficult to ask them to use the framework and to be active in the process of learning in parallel with the presidential studies. We were forced to test our framework with a small number of learners.

We are aware that these preliminary results are not decisive. It remains for us to finalize the development of all the components of the system, add other courses, create courses, and involve many learners. Also, we will implement the fuzzy AHP and give a comparison of the two approaches.

4 Conclusions

In this work, we have proposed an overview of our framework based on Analytic Hierarchy Process (AHP) algorithm for an adaptive learning through the existing MOOCs. This suggested framework uses a variety of aspects including choice of learning path, learner satisfaction, and achievement to present an adaptive list of existing MOOCs to a learner.

We presented the preliminary results demonstrating the success of this framework in listing the most suitable MOOCs to a specific learner. For further validation, first, we plan to involve other members to our engineering team and implicate more learners in the evaluation of all components and improve our proposal based on the results of the assessments and feedback from these learners. Second, we plan to improve the pedagogical model, including more materials to make learning more efficient and attractive.

References

1. Afa, Y., Battou, A., & BAZ, O. (2017). Toward the MOOC capitalization using fuzzy analytical hierarchy process. *The International Journal of E-Learning and Educational Technologies in the Digital Media (IJEETDM)*, *3*(2).
2. Aissanou, F. (2012). *Décisions multicritères dans les réseaux de télécommunications autonomes*. HAL.
3. Ben Mena, S. (2000). Introduction aux méthodes multicritères d'aide à la décision. *Biotechnology, Agronomy and Society and Environment*, *4*(2), 83–93.
4. Bernardin, E. (2014). Business model for MOOCs: a perspective of reusability,. In *E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*. New Orleans.
5. Hammami (2003). *Modelisation Technico-Economique D'une Chaine Logistique Dans Une Entreprise Reseau*. PhD thesis.
6. Hua, Z., Gong, B. X., & X. (2008). A DS–AHP approach for multi-attribute decision-making problem with incomplete information. *Expert Systems with Applications*, *34*, 2221–2227.
7. Keeney, R., & Raiffa, H. (1976). *Decisions with multiple objectives: Preferences and value tradeoffs*. New York: J. Wiley.
8. Navneet, B., & Kanwal, R. (2004). *Strategic decision making: Applying the analytic hierarchy process* (1st edn.). Springer.
9. Park, Y. (2011). A pedagogical framework for mobile learning: Categorizing educational applications of mobile technologies into four types. *The International Review of Research in Open and Distributed Learning*, *12*(2), 78–102.
10. Reich, J. (2014). MOOCs and the science of learning. *Education Week*.
11. Roy, B. (1985). *Méthodologie multicritère d'aide à la décision*. Ed. Economica.
12. Saaty, R. W. (1987). The analytic hierarchy process – what it is and how it is used. *Mathematical Modelling*, *9*, 161–176.
13. Saaty, T. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, *48*, 9–26.
14. Saaty, T. (2007). Time dependent decision-making; dynamic priorities in the AHP/ANP: Generalizing from points to functions and from real to complex variables. *Mathematical and Computer Modelling*, *46*, 860–891.
15. Vargas, R. V. (2010). Using the analytic hierarchy process (AHP) to select and prioritize projects in a portfolio.
16. Zouggari, A. (2011). *Une approche couplant logique floue et capitalisation des connaissances pour la résolution du problème de choix des fournisseurs soutenues*.